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Department of Financial Economics

Master Thesis

The Impact of Credit Rating Events on Credit Default Swap Spreads throughout the Financial Crisis (2007-2009)

Evidence from the global market

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Abstract

In this paper, I analyze the effect of credit rating events on the credit default swaps markets in three periods: before, during and after the most recent global financial crisis. I find that in the majority of the cases, rating agencies tend to be anticipated by the credit default swaps market. Finally, I conduct a logistic analysis that allows me to estimate whether movements in the credit default swaps market have forecasting power with regards to the credit rating events. I find evidence in favor of this in all the events except for positive reviews.

keywords: credit rating agencies, credit default swaps, crisis, event study, logistic modeling

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1 Introduction

Credit rating agencies play a major role in assessing the credit risk of debt securities as well as their issuers. They were highly scrutinized during the most recent global financial crises due to the overvaluation of securities that were then downgraded to the junk level. There are three big rating agencies that control almost all the industry: Moody's Investors Services, Standard and Poor's which together control 84 % of the global market and Fitch that controls 13 % of the global market. The remaining part consists of small rating agencies (SEC, 2016).

Another element that received particular attention during the global financial crisis was the credit default swap market. A credit default swap (hereafter CDS) is a contract in which the seller of the CDS will compensate the buyer (usually the creditor) in case of default or another credit event by the reference entity, which is the debtor. Thus, it can be compared to an insurance against credit risk. In practice, the buyer makes periodic payments to the seller who guarantees in return to sell a bond equal to the face value of the bond of the reference entity in case a credit event occurs. The yearly rate of payments is defined as the CDS spread. Once a credit event occurs, the buyer of the CDS stops paying the swap premium and he receives the terminal value, which is usually a specified amount of the face value of the bond. There are three types of credit events that characterize a default: failure to pay in which the reference entity fails to make a scheduled interest or principal payment; write-down, which means that principal of the obligation of the reference entity is deemed unrecoverable and finally the downgrade of the obligation of the reference entity to a rating of CCC/Caa2 or lower (Fabozzi, 2013).

In this paper I delve into the relationship between credit default swaps spreads and credit rating actions. I analyze three credit rating events: announcements, reviews and outlooks. A credit rating change announcement is the change of a credit rating on an obligation, a review for a credit change is a warning for investors that the credit rating of a certain obligation might change in the next 90 days, whereas an outlook is a warning that the credit rating might change in the next two years. I analyze and compare Moody's and S&P's. The research question for this paper is the following:

Did the impact of credit rating events on credit default swaps market change throughout the global financial crisis?

In order to answer the research question I apply the event study methodology with data retrieved both from Bloomberg and Datastream. I compile a list of companies that belong to the S&P Global 1200 Index from 2003 till 2017.

Like other papers I find scarce evidence in favor of the thesis that credit rating events hold a powerful informational content as the market seems to perceive changes in rating well before the agencies issue their decision on the creditworthiness of a firm's obligation. Furthermore, I perform a cross sectional analysis focusing on the event window. I find that the announcement of downgrades is accompanied by an increase in the cumulative abnormal return, which is 1.278 basis points higher than upgrades on the day of the event. In the case of reviews, I find that the announcement of negative reviews is accompanied by an increase in the cumulative abnormal return, which is 2.060 basis points higher than positive reviews on the day of the event. The fact that the impact of reviews is larger than the impact of downgrades could be explained by the fact that reviews are not as unanticipated as downgrades. When adding the effect of the crisis, including a dummy variable that takes on value 1 between 2007 and 2009 and 0 otherwise,the impact of downgrades is magnified by 1.447 basis points. Finally, I construct a logit model that allows me to forecast the probability of a future event given the previous movements in credit default swap prices. In fact, I show that changes in credit default swap spreads seem to be useful at forecasting the probability of an event, in particular of negative reviews.Specifically, I find that an increase of one basis point in the monthly average of the daily changes of credit default swap spreads increases the probability of a downgrade by 25.5% and reduces the probability of an upgrade by 37.9%.

This study is innovative because it merges two main studies on the topic. I apply the hypotheses of Steiner & Heinke (2001) to the methodology of Hull et al. (2004). This not only allows me to expand the latter study from a geographical perspective as I use international evidence, but also from a temporal perspective since I include a new variable to their analyses, which is the crisis period. In practice, I find that the crisis amplifies the effect of the announcements only in the case upgrades and downgrades in the cross sectional analysis. On the other hand, the t-statistics show that during the crisis the announcement day effect is much larger than during the precrisis and post crisis period, but only for downgrades and negative reviews. The same holds for the anticipation effect.

The following sections are structured as follows: the first contains the theoretical background behind the research question, the second one contains the hypotheses that I address in this research paper, the third a description of the dataset, the fourth the methodology implemented, the fifth includes the interpretation of the results retrieved from the quantitative analysis and the last presents the conclusive remarks.

2 Literature Review

The question of whether credit ratings have significant informational content has been long investigated by the financial literature. These studies can be gathered in three large groups: the first analyzes the information content of credit ratings on stock prices, the second one on bond prices and the third one on CDS spreads. All three branches seem to agree with the fact that there is a paradox within the credit rating industry. Credit rating agencies seem to be very powerful and their ratings very influential since they are used in different types of financial transactions, from corporate to sovereign, as well as regulatory, such as in the determination the minimal capital requirements. However, the majority of the papers concurs with the fact that they have been shown to lag and not lead the market, which means that the market anticipates a change in credit rating. Thus, credit ratings seem to have little incremental informational value. In this paper, my main focus is on the informational value of credit ratings with reference to the CDSs market.However, as this study is inspired by all the three branches, it is necessary expose the main findings.

2.1 Credit Ratings and the Stock Market

In theory upgrades or positive credit ratings announcements should be accompanied by a positive stock price reaction, whereas downgrades by a negative one. One of the first studies in the field finds support for this, however it points out that credit rating agencies lag the stock market. They show that higher and lower abnormal returns were expected before the announcement of a credit rate change. In particular, they find a lag of 15-18 months in the absence of company-specific events (Pinches & Singleton, 1978). This study is quite exceptional since it is one of the few that finds a significant market reaction for positive credit ratings changes.

Another study that investigates the impact of the press release of a credit rating change on common stock returns shows that there is a negative response in stock returns in the case of a downgrade, but finds little significant positive abnormal return in the case of an upgrade. Also, it presents the analysis of the impact of the addition of a company to the credit watch by Standards and Poor's. The results indicate that there is a negative response in case of the possibility of a downgrade and a positive response in case of a potential upgrade (Holthausen & Leftwich, 1986).

These results seem to be partially confirmed by another study which shows that there is a statistically significant negative stock return reaction in case of a downgrade, but no significant positive stock return in case of an upgrade. The authors of the study also find that the average excess stock return is significantly more negative for firms in the below investment grade rating class than in the investment grade class. This is commonly known as the investment grade effect and it also applies to the bond and credit default swaps market. Additionally, in line with the previous study, they find a negative stock market reaction in case of a negative credit watch, which translates into the possibility of a downgrade. Differently, they do not find a positive stock market reaction in case of a positive credit watch (Hand et al., 1992). Consistent with the before-mentioned studies, Norden & Weber (2004) find a negative stock market reaction in case of a downgrade, but no statistically significant positive stock market reaction to upgrades. They also notice a lagged reaction in credit ratings announcements in the sense that there are negative stock returns prior to the announcement day and a stronger effect for companies that belong to the below investment grade rating class. The innovative aspect of this study is that it compares the information content of credit ratings announcements with analysts earnings forecasts. They find that downgrades are already partially incorporated in the stock prices and earnings forecasts and thus have a tendency to lag them, but they also tend to provide new information since there are changes in the stock returns even after the announcement grades and analysts tend to revise their forecasts in a negative way.

Another research paper that examines the long-run impact of Moody's credit rating announcements on stock returns points out the fact that the underperformance due to downgrades is stronger during the first few months post-announcements but it can be noticed even though to a lesser extent for an entire year and it ranges between minus 10-14 %. The authors of the study find that small and low credit firms are more affected by downgrades. Like prior studies, they do not find any significant effect for upgrades (Dichev & Piotroski, 2001). Another study that tries to apply similar analyses to the G7 countries stock markets finds that upgrades do not have additional information content and downgrades do have a statistically significant negative effect on stock prices in all the countries. Rating changes within one investment class have a lower information content than rating changes across different classes, i.e. from investment grade to speculative grade, (Hu et al., 2016).

In sum, most studies seem to find a statistically significant stock market reaction in the case of downgrades, whereas there is mixed evidence in the case of upgrades and reviews in both directions.

2.2 Credit Ratings and the Bond Market

The information content of bond rating changes has been studied from different point of views. One of the first studies on the topic analyzes the difference in reaction to rating classifications between the utility bond market and the industrial bond market and it shows that the industrial bond market leads a rating change, whereas the utility bond market does not. They also find that the longer the maturity of the bond the bigger the reaction to a negative credit rating change announcement (Grier & Katz, 1976).

Another study finds no statistically significant market reaction to a credit rating change, which is attributed to the fact that bond ratings can be estimated from publicly available information. These results are corroborated by the fact that corporate bond prices change before the rating change (Weinstein, 1977). However, the findings are strongly contradicted by many other papers. An analysis on the reaction of municipal bonds to rating changes shows that the bond prices change during the month of the rating change and there is no prior reaction (Ingram et al., 1983). A research paper on state bonds shows that there is a partial significant impact of credit ratings events on bond prices (Liu & Thakor, 1984).

A paper on corporate bonds demonstrates that there is a statistically significant negative bond price reaction after the announcement of a downgrade as well as after the announcement of an upgrade. However, the authors find an asymmetry between the size of the negative average excess bond return in case of a downgrade and the size of the positive average excess bond return in case of an upgrade, where the former is bigger than the latter. The study also investigates the impact of an addition to a Credit Watch by Standard and Poor's and concludes that the size of the average excess bond returns is symmetric for both the possibility of a downgrade and an upgrade (Hand et al., 1992). Another study investigates the effect of information arrival due to bond rating changes on institutional bond pricing. The authors conduct cross sectional regressions to assess whether a credit rating change reveals additional information and they conclude that downgrades affect bond prices especially if an across-class decrease in rating occurs. They also investigate whether there is a different reaction for companies that were placed on the Credit Watch prior to the announcement and companies that were not. The empirical evidence does not confirm this hypothesis and there is no reaction around a Credit Watch. Moreover, in line with the prior study, they find an asymmetry in the average excess stock return between upgrades and downgrades. They also conclude that industrial firms experience a larger price adjustment after a credit change than public utility firms (Wansley et al., 1992).

Hite & Warga (1997) find that there is a positive excess returns of industrial bonds when an upgrade from non-investment to investment grade occurs, but not in any other circumstances. They present the strongest evidence of additional information content in the case of a decrease in rating from the investment grade to the below investment grade. Additionally, downward changes within the investment grade class have a lower effect. However, both are strongest in the 6-month lapse before the rating event and in the month itself. This also applies to upgrades from below investment grade to investment grade. The authors also check whether there is a difference in bond prices according to the agency who initiates the downgrade six months earlier. They find that for non-investment grade bonds, Moody's has a stronger price effect, whereas S&P does not have it.

Another study finds evidence which partially contrasts with the 1997 paper since it shows no reaction for upgrades and positive reviews, but it indicates a strong reaction for downgrades and negative reviews, which lasts also for three weeks after the announcement. It shows negative excess returns before the announcements and positive excess returns after. Additionally, the authors document that the price reaction is much larger when the rating crosses the investment grade barrier (Steiner & Heinke, 2001).

A more recent study that analyzes the reaction of bond prices in small economies to downgrades and upgrades during the financial crisis shows that the bond market does not respond to positive announcements and negative reviews. However, it is sensitive to downgrades.Similar results are documented by Steiner & Heinke (2001). Between 2000 and 2007 the reaction to downgrades is small but significant, whereas in the 2008-2009 periods the negative reaction is larger but it is followed by a correction (Afik et al., 2014). Finally, a research paper analyzes whether the implementation of watchlists by Moody's in 1991 leads to a stronger bond market reaction and they find supportive evidence of this in the case of downgrades. Besides, the authors state that this enhances the monitoring function performed by credit rating agencies.(Bannier & Hirsch, 2010). All in all, the literature on bond prices does not contrast the one on the stock market as most studies seem to agree with the fact that negative credit rating events are associated with a statistically and quantitatively significant market reaction. It is interesting to highlight the difference between investment grade and speculative grade bonds, which is carried on in the present paper.

2.3 Credit Ratings and the Credit Default Swaps Market

My decision to use credit default swaps is motivated by several reasons. The first reason is that they are relatively new instruments which played a very important role due to their connection to other types of securities in the recent financial crisis. The second one is that the literature on their relationship with credit ratings is not as abundant as the one on bonds and stocks. The third reason is methodological. Hull et al. (2004) mention two important reasons. Firstly, credit default swaps pricing is more accurate than bond yields because it is based on precise bid-ask quotes, given by a dealer who commits to trade the principal at this price. In the bond market, there is no commitment. Secondly, credit default swaps spreads do not require an assumption on the risk free benchmark in order to compute the abnormal return, whereas bonds do. The study conducts two types of analysis: an event study that focuses on the relationship between credit default swaps and credit rating announcement and a maximum likelihood analysis, which estimates the probability of a negative credit rating event conditional on the changes in the credit spread in the month prior to the event.They do not focus on other events because they do not find statistically significant results. In the event study, they investigate six types of rating events: downgrades, upgrades, reviews for an upgrade, reviews for a downgrade, positive outlooks and negative outlooks. They find that credit spreads have a positive reaction before all three types of negative rating events, but only reviews for a downgrade present an announcement day effect. They do not find any statistically significant post-announcement day effect. With regards to positive credit rating events, they do not find any statistically significant effect for any of the cases. In their second analysis, they estimate that the probability of a negative credit rating events conditional on spread changes is 42.6% for all the downgrades in the sample, 39.9% for all reviews for a downgrade and 50.9% for all the negative outlooks.

A similar research paper, which investigates the relationship between credit rating announcements and the credit default swap market as well as the stock market, shows that downgrades are anticipated by both markets. However, the credit default swap market tends to react earlier than the stock market in the case of reviews for downgrades. This study integrates the above mentioned one because it also studies Fitch's ratings, though it does not find any significant effect on either market. On the other hand, reviews for downgrades by Moody's and Standard & Poor's are related to abnormal performance, while announcements for a downgrade are not. This finding is similar to the one by the paper described prior (Norden & Weber, 2004). A more recent study expands the Hull et al. (2004) research by using a more recent dataset and by incorporating a new variable: the state of the economy. In line with prior studies, they find that downgrades, reviews for downgrades and negative outlooks are accompanied by abnormal reaction. Contrary to the other papers, they find that upgrades, reviews for upgrades and positive outlooks are accompanied by statistically significant announcement effects, although these effects are smaller than the ones documented for downward actions. They estimate that the upgrade effect is much larger for non investment grade companies, whereas the downgrade effect is much larger for investment grade companies. Moreover, the authors find that after controlling for previous credit ratings events, both reviews and outlooks in both directions are accompanied by abnormal returns on the announcement day and they do not seem to be anticipated by the market. Furthermore, they find that both non-investment grade and investment grades related credit default swap spreads are useful in predicting the likelihood of a downgrade, a negative review and a negative outlook. However, they did not find significant results for positive news. They also find that due to a fear factor and other macroeconomic conditions that help measure the state of the business cycle, the effect of upgrades is much stronger during recessions than during periods of economic upturns (Finnerty et al., 2013). Similarly to the other fields of research, the papers described in this section tend to agree with the fact that negative events are connected to a stronger abnormal performance and that the reaction is magnified or shrunk according to the state of the economy, which is a new element in the literature.

3 Hypotheses

In order to investigate the research question, I check the following hypotheses in line with Steiner & Heinke (2001) and apply them to the CDS market.

3.1 Information Content Hypothesis

Rating actions contain valuable and non-public credit information, any announcement of these rating actions should result in a subsequent price change of the corresponding credit default swap spread. The move in price should be permanent, since there is a new risk level associated with a down- or upgraded bond. If the assessment of rating agencies is correct, the price reaction should be stronger the more notches are crossed in case of a rating change (Steiner & Heinke, 2001). They do not find significant results in this regard. In their results they find that changes in the valuation of downgraded bonds do not occur only on the announcement day and in the following days but also in the days prior to the announcement. This may lead to the conclusion that credit rating agencies tend to lag and not to lead the market. They also notice a rebound effect in the third week from the announcement day. The interpretation is twofold: either the market overreacts to downgrades and it corrects the expectations afterwards or there is some sort of regulatory pressure towards the bond markets that drives the prices down. The reason why there is an asymmetric reaction between downgrades and upgrades is that credit rating agencies have an asymmetric loss function whereby their loss in reputation is much higher if they report too high a rating, rather than too low. Hull et al. (2004) find similar results, but they apply them to the CDS market. I expect to find similar results when studying into the credit default swaps with reference to downgrades, but possibly significant results in the case of upgrades as found by Finnerty et al. (2013) who use a more recent dataset.

3.2 Issuer Nationality Hypothesis

If US based rating agencies acting on the international market lack the acquisition of knowledge about country-specific credit standards, then ratings of non-US bonds can be expected to be less informative than ratings of US bonds. If true, US bonds should manifest a stronger reaction than international bonds. In order to test it, Steiner & Heinke (2001) create two samples: one of bonds whose issuer is settled in the USA and one of bonds whose issuer is set elsewhere. Their result is supportive of the nationality hypothesis. Since I also analyze the two biggest US based rating agencies I expect to find similar results in the case of credit default swaps markets.

3.3 Reliability Hypothesis

The international bond market does not have different reactions whether the rating has been given by one agency or another. The authors find any evidence in favor of this hypothesis. I expect to find similar results.

3.4 Price Pressure Hypothesis

When a bond falls into speculative grade, regulators force investors to sell the bond. They do find a stronger price reaction when a bond is downgraded from investment grade to speculative grade. Hull et al. (2004) find similar results in the case of CDS spreads.

On the other hand, Finnerty et al. (2013) find that the market reacts to both rising stars (a crossover to the investment grade) and fallen angels (a crossover to speculative grade). They attribute the market surprise with regards to upgrades to the fact that such upgrades are less monitored than downgrades. I expect to find similar results to last group of authors.

3.5 Forecasting Power Hypothesis

If a rating event is anticipated by the market, it could be that changes in credit default swap spreads are good predictors of its occurrence (Hull et al., 2004). The group of authors finds that 42.2% of downgrades, 39.8% of all reviews for downgrades and 50.9% of negative outlooks come from the top quartile of credit default swaps. Finnerty et al. (2013) finds that credit default swaps in both the investment grade and non-investment grade are useful to estimate the probability of downgrades but not upgrades. I hope to find similar results.

4 Data and Descriptive Statistics

4.1 Sources and Merging Process

In this paper I analyze credit default swaps of companies that belong to the S&P Global 1200 index. Even though there are more global indexes, I use this one because I do not have the permission to see the constituents of bigger indexes such as the MSCI Global and the FTSE All World. I use Bloomberg to find the index constituents by checking the list at the end of each year from 2003 to 2017 and I eliminate duplicates. This allows me to limit the survivorship bias in my sample. I come up with a list of 436 companies from which I obtain the international security identification number (ISIN). This code is helpful because it can be used to retrieve data from other databases, such as DataStream. From the list of ISINs, I obtain the DataStream tickers from which I obtain the codes of the daily 5 years corporate credit default swap spreads quoted in U.S dollars. There are two sources of data for CDS spreads within DataStream: CMA DataVision and Thomson Reuters CDS. The latter starts at the end of 2007, whereas the former starts in 2004 and finishes in 2010. Thus I use CMA Datavision from 2004 till the end of 2007 and Thomson Reuters CDS from the end of 2007 till the December 2017. In order to merge the two databases, I convert the CMA DataVision codes to Thomson Reuters codes by using the appropriate table on the Datastream website, which is linked below. A Datastream code for a CDS spread is composed of the company's ticker, the maturity, the currency and a variant code that indicates the type of credit event. I choose the denotation AR that yields the most data since the differences in the spread values between using one variant or another are minimal. I eliminate the companies that do not have data for any of the years from 2004 till 2017.

After this, by using the ISIN codes of the remaining companies I retrieve the data on credit rating events from Bloomberg by linking back the ISIN codes to the Bloomberg tickers. I get the data for two credit rating agencies: Moody's and Standard and Poor's. I intend to investigate three types of rating activities: long term ratings, reviews and outlooks. Bloomberg does not store information on historical outlooks, which does not allow me to investigate the impact of changes in outlooks on credit default swap spreads. Therefore my analysis is confined to credit rating changes and reviews. I use Bloomberg because it is the most complete database for historical credit ratings. Compustat only contains S&P ratings; Datastream reports historical and current ratings for S&P and only current ones for Moody's; Mergent FISD focuses only on US companies; Thomson One reports only credit ratings and no other credit rating action. However, on Bloomberg Moody's long term ratings contain data that is not pertinent to our research questions, since some ratings are attributed to more specific qualities of debt such as short-term and long-term counterpart risk and speculative grade liquidity. On the other hand, S&P long term ratings are long term issuer ratings. To achieve greater conformity with S&P long-term ratings, I use Moody's issuer ratings as well even though this yields less observations. I remove the duplicate ratings by date and company and I drop around 84000 observations. After merging the databases, there are some unmatched observations. I keep all the observations in the file containing credit default swaps observations and I delete the credit ratings information that do not match with the credit default swaps, around 800. In total I am left with approximately one million observations.

4.2 Descriptive Statistics

In total, I obtain 1931 ratings of which 1155 were issued by S&P and the remaining 776 by Moody's I find 1041 downgrades and 642 upgrades. The ratings are accompanied by 1018 reviews of which 746 are given by S&P. I find that 43 are developing, which means that the rating agencies did not give a clear assessment about the direction of the possible rating change, 752 are negative and 223 are positive. After merging, I get 1663 credit events of which 646 are downgrades, 473 upgrades, 402 are negative reviews and 142 positive reviews. These results are shown in **??**.

Table 1: Summary statistics of the credit default swaps spreads by period and by event.

	Period											
Event	**Precrisis**			**Crisis**			**Post crisis**			**Total**		
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Downgrade	112	105.343	97.810	227	215.443	122.887	307	188.613	117.002	646	169.800	112.566
Upgrade	108	55.566	50.990	94	109.387	102.942	271	134.858	98.594	473	99.937	84.175
Negative Review	95	80.620	77.381	141	188.652	121.5911	166	150.407	109.540	402	139.893	102.837
Positive Review	40	54.390	49.952	33	107.342	104.3752	69	150.218	109.468	142	103.983	87.932
Total	**355**	**73.980**	**69.033**	**495**	**155.206**	**112.949**	**813**	**156.024**	**108.651**	**1663**	**128.403**	**96.878**

I find that the average credit rating in the sample is BBB+ in the merged database. I split the time frame into three periods: pre-crisis (from 2004 till 2006), crisis (from 2007 to 2009) and post crisis (from 2010 till 2017) and I present the frequency of upgrades, downgrades and reviews by period. I find that the number of credit rating events is higher in the post crisis period than in the crisis period as the former includes more than twice the amount of years as the latter. I do the same for the CDS spreads and I find that the average CDS spread before the crisis is 73.98 basis points, during the crisis is 155.206 basis points and after the crisis is 156.024 basis points. I also notice that the volatility, measured by the standard deviation, is much higher during the crisis (112.949) than during the precrisis (69.033) and the postcrisis (108.651). This could imply a higher riskiness. In addition, I find that the average credit spread is much higher with downgrades and negative reviews than with upgrades and positive reviews as the mean value of the negative events is 160.800 and 139.893 whereas the mean value of the positive events is 99.137 and 103.983 respectively as shown in the last column of **??**.

This could be a sign of the higher credit risk associated with downgraded or negatively reviewed obligations. I also find that the average credit spreads are higher in the case of negative events during the crisis than in other periods, whereby the average of credit default swap spreads is 215.443 in the case of downgrades and the average of credit default swap spreads is 188.652. This implies that during the crisis the announcement of negative news was likely to be accompanied by an augmented reaction in comparison to other periods, which could be explained by the increased credit risk.

I also check whether the average CDS spread is higher when a bond is downgraded or negatively reviewed in lower rating classes and I find evidence in favor of this, although they do not increase consistently. The greatest value (342.110) for downgrades is in the lowest rating group (23). On the other hand, when the upgrades or positive reviews occur in the top rating classes the average credit spread decreases dramatically. The lowest value for upgrades is in the highest rating group (1). These results are presented in Table 2.

Furthermore, I can see that the average credit default swaps spread related to investment grades issuers (above rating number 11) is significantly smaller than the one related to the speculative grades issuers (below rating number 11). This is due to the fact that CDS spreads in the speculative grade class are linked to high-risk bonds, which are likely to be insolvent. Thus the CDS spread is higher as it needs to compensate for this. Moreover, I notice that downgrades have a larger impact (mean value 286.571) for the below investment grade group, which is equivalent to a rating equal and below Ba1 for Moody's and a rating equal and below BB+ for S&P. These results are presented in Table 3.

Table 2: Summary statistics of CDS spreads across rating classes.

Ratings	Downgrade		Negative Review		Positive Review		Upgrade		Total	
	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
1			6	29.450			1	35.300	7	32.375
2	3	35.453	7	118.863			5	49.050	15	67.789
3	9	83.978	9	81.012	2	26.000	14	49.129	34	60.030
4	25	117.357	19	101.510	5	26.000	23	51.228	72	74.024
5	31	113.744	38	121.167	7	57.764	27	44.582	103	84.314
6	43	134.375	53	116.587	8	55.700	41	72.441	145	94.776
7	68	111.951	59	95.188	9	41.680	72	72.167	208	80.246
8	81	110.333	71	118.093	20	46.138	78	86.063	250	90.157
9	99	160.053	59	155.856	24	88.570	71	104.469	253	127.237
10	92	187.301	29	231.515	20	106.609	45	118.111	186	160.884
11	40	239.086	15	234.443	11	107.620	29	166.993	95	187.035
12	34	261.417	11	261.523	8	176.227	24	204.727	77	225.974
13	40	278.187	11	326.198	6	148.750	20	256.219	77	252.339
14	27	318.041	7	330.851	10	253.177	9	268.048	53	292.529
15	21	331.853	5	320.766	3	260.053	6	306.407	35	304.770
16	12	333.591	1	280.670	5	265.746	3	342.110	21	305.529
17	7	342.110	1	342.110	3	342.110	3	342.110	14	342.110
18	5	297.988			1	342.110	2	342.110	8	327.403
19	1	342.110							1	342.110
20	2	342.110	1	342.110					3	342.110
22	2	231.805							2	231.805
23	4	342.110							4	342.110
Total	646	224.522	402	200.439	142	146.516	473	161.737	1663	186.005

Table 3: Summary statistics of CDS spreads by investment grade and speculative grade.

IGSG	Event	N	Mean	Sd
INVESTMENT GRADE	Downgrade	451	139.084	106.254
	Upgrade	377	82.126	69.009
	Negative Review	350	126.743	104.105
	Positive Review	95	69.344	62.385
SPECULATIVE GRADE	Downgrade	195	286.571	89.264
	Upgrade	96	227.796	100.538
	Negative Review	52	285.889	82.670
	Positive Review	47	202.026	111.845

5 Methodology

5.1 Defining Credit Ratings Events

In this paper I investigate the relationship between credit default swaps spreads and credit rating changes announcements. I define a credit event in four different ways: upgrade, downgrade, negative reviews and positive reviews. In order to quantify a credit event, I need to transform the credit ratings from both agencies into numerical variables. The highest rating takes on value 1 and the lowest takes on value 23. However, since Moody's does not offer a D or SD rating, I only have 21 values for that rating agency.

The Bloomberg datasets attaches the reviews symbols to the credit ratings. Both agencies quantify a positive review as "*+" and a negative review as "*-". Thus, I separated the last two symbols from the credit rating itself in order to distinguish whether the credit event was a credit rating change announcement or a review for a credit rating. Thus, I define a change in rating as the difference between the current and previous rating, whenever this is different from 0. If the difference between the current rating and the previous rating is larger than 0, then I define the event as a downgrade. If the difference between the current rating and the previous rating is smaller than 0, then I define the event as an upgrade. If the difference is equal to 0 and the current rating is accompanied by "*-" or "*+", I define the event as a negative credit rating review or a positive credit rating review respectively.

5.2 The Event Study Methodology

The most appropriate statistical tool of studying the impact of credit rating events on credit default swap spreads is the event study. The procedure to conduct an event study is as follows: first, I need to define the event that interests me, in this case a credit rating event, which corresponds to day 0.

Second, I need to construct the event windows, which consist of the amount of days surrounding the event, where the abnormal returns are calculated.

Third, I create the estimation windows which serve the purpose of analyzing the normal performance of the credit default swaps prior to the event. The day of the event is not included in our estimation window. I also compute a post-estimation window, which I use to check how credit default swap prices react to the event. The first and most important step of the event study is to compute the abnormal returns, which are calculated as follows:

$$AR_{it} = \begin{cases} Spread_t - Spread_{t-1} - (Index_{nt} - Index_{nt-1}) & \text{if } t >= 0 \\ Spread_t - Spread_{t-1} - (Index_{ot} - Index_{ot-1}) & \text{if } t < 0 \end{cases} \tag{1}$$

where AR_{it} is the abnormal return of company i at time t. The spreads represent the daily difference in the credit default swap spreads of company i at time t. The index term in the first line of the formula represents the cross sectional average at time t of the credit default swap spreads belonging to the same credit rating as company i before the announcement day. The index term in the second line represents the cross sectional average of all the credit default swap spreads belonging to the company with the same credit ratings as firm i on and after the credit rating event t. In the calculation of the index I exclude the credit spread on the date of the event in order to better represent the average behavior of the credit default swaps. Adjusting for the index allows to adjust for the average default risk for every credit rating class and represents the market factor when computing the abnormal return. After this, I compute the cumulative abnormal return (CAR_{it}) for each company by summing the abnormal return throughout the event window in the following fashion:

$$CAR_{i[t_1;t_2]} = \sum_{t_1}^{t_2} AR_{it} \tag{2}$$

Afterwards, I present the development of CAR before and after the rating event. Thus I construct several time windows in which I measure the CAR. I define the date of a credit event as day 0 and I compute the amount of observations before and after the events for each company. These time intervals may include other events both of a different type and from a different agency. Thus, the windows may be contaminated. I use the following windows: [-90; -61], [-60; -31], [-30; -2], [-1;1], [2;30], [31;60] and [61;90] for all the credit events following Norden & Weber (2004). These windows are constructed in such a way so that they show the monthly development of the credit default swap market before and after the event.

5.3 Operationalization of the Variables

Specifically, these tests allow me to investigate the information content hypothesis and whether credit rating agencies tend to lag or lead the market. Moreover, I delve into this matter more deeply by checking whether the size of the upgrade/downgrade matters by creating a dummy that takes on value one when the absolute value of the difference between the current and previous rating is equal to one and 0 if it is larger than 1.

I test the issuer nationality hypothesis by constructing a dummy variable that takes on value one if the issuer is USA based and 0 otherwise.

Furthermore, I want to test the reliability hypothesis by checking whether there is a different abnormal return according to the agency who made the announcement. Again, I construct a dummy variable that takes value one if the rating is given by Standard and Poor's and takes value 0 if it is given by Moody's.

I investigate whether there is a difference in abnormal returns between fallen angels, which entail a downgrade into speculative grade and rising stars, which entail

an upgrade to investment grade. Both agencies consider that the boundary between investment and speculative grade starts at rating 11 which corresponds to BB+ for S&P and Ba1 for S&P.
Last, I construct a dummy variable to control for the crisis, which takes on value 1 if that is the case and 0 otherwise.

5.4 Univariate Hypothesis Testing

I conduct two types of T-tests. First I run a one-sample T-test to analyze the size and the direction of the cumulative abnormal returns in the estimation window, in the event window and in the post-estimation window as well as apply these to the pre-crisis period, crisis period and post-crisis period. However, in order to make sure that these results are valid, I need to check whether the assumptions are met. The assumptions for the one sample T-tests are: the dependent variable must be continuous, normally distributed and the sample is a simple random sample.

As the dependent variable is continuous and the data contains observations that are equally likely to get selected for the analysis, I only have to test the normality assumption. I do so by performing the Jacques-Bera test for departure from normality, where the null hypothesis is that the data are normally distributed. As the p-value is 0.000, I have to reject the null hypothesis. However, since I have quite a large sample size (n>=40), I can safely assume that my observations are approximatively normally distributed. The standard errors, an indication of the margin of error in the confidence intervals, are computed by dividing the standard deviation by the square root of the sample size (Moore et al., 2011). I also check whether there are significant differences in the pre-crisis period, in the crisis period and in the post-crisis period. Here, I check the null hypothesis that the cumulative abnormal return ($CAR_{i[t_1;t_2]}$) is equal to 0.

Second, I run a T-test for independent samples using the dummy variables constructed above. Thus, I investigate the hypotheses by comparing the means of the cumulative abnormal returns within the two samples during the event window. Here, besides the assumptions verified above, I need to ascertain whether the variances are equal across the samples. Since the dependent variable is not normally distributed, I run the Levene's test for equal variances which is more robust to non-normality that other tests (Gastwirth et al., 2009). I cannot reject the null hypothesis that the variances are homogeneous across samples. All the results of the tests described in this section are illustrated in the Appendix.

5.5 Regressions

I conduct two types of regression analysis. I use the cumulative abnormal returns in the [0,1] window as the dependent variable for either upgrades or downgrades and I use the variables described above in the regression model that follows. I build the following model gradually by adding one variable at a time to check whether they add significant explanatory power to the model. The complete model is as follows:

$$CAR_i = \beta_0 + \beta_1 REVENT_i + \beta_2 SIZE_i + \beta_3 USA_i + \beta_4 AGENCY_i + \beta_5 IGSG_i + \beta_6 CRISIS_i + \epsilon_i \quad (3)$$

Where $REVENT_i$ takes on value 1 if the event is a downgrade and takes on value 0 if it is equal to a downgrade and ϵ represents the error term. The remaining variables are defined as above.

The second type of regression regards the reviews of a credit rating. For this, I need to construct a dummy variable, $REVIEW_i$, that takes on value 1 if the review is negative and 0 if it is positive. The model is identical to the one above except for the size variable that is excluded because a credit rating review does not entail a change in credit rating but it only gives an outlook of a possible movement in either direction. Similarly, the variables are added stepwise so that I can ascertain whether there is incremental significance in my model. The complete model is as follows:

$$CAR_i = \beta_0 + \beta_1 REVIEW_i + \beta_3 USA_i + \beta_4 AGENCY_i + \beta_5 IGSG_i + \beta_6 CRISIS_i + \epsilon_i \quad (4)$$

5.6 Assumptions of the Error Term

In order to make sure that the regression model is valid I need to check whether the assumptions for the validity of a linear regression model hold. First of all, I need to check whether the errors are normally distributed. I do this by conducting the Shapiro-Wilk test and I find evidence against this. This implies that some observations influence the regression results more than others, thus making the regressions coefficient less reliable. After, I check whether there is homoskedasticity of the error terms with the Breush-Pagan test, in other words whether the error term has constant variance across observations. The test results show that there is evidence against homoskedasticity. I conduct the White test because it relaxes the assumptions that the error terms must be normally distributed, like in this case. The results show that I cannot reject that the the error terms are homoskedastic. Secondly, I check whether there is evidence for serial correlation. In order to do this I conduct the Wooldridge test for panel data and I find evidence that there is significant first order autocorrelation. For these reasons, I use robust standard errors so that I get valid results despite heteroscedasticity and autocorrelation. At last, I test whether there is evidence for perfect multicollinearity by computing the variance inflation index (VIF) and I do not find evidence in favor of this as the VIF is smaller than 10. These results are reported in the Appendix.

5.7 Logistic Modeling

In case I find significant evidence that credit rating agencies tend to lag the market, I run a logistic model that allows to estimate what the probability of a credit event attributed to changes in credit default swaps spreads. In order to do this, I construct a probability function that allows to estimate that. I first construct 30 days interval for each company in which no credit event has occurred as well as the mean spread in that time interval. Then, I check whether a credit rating event occurs in the next 30 days. The probability function is shaped as follows:

$$P = \frac{1}{1 + e^{-a-bx}} \tag{5}$$

where x is the average spread in the time interval and P is the probability of a rating event in the 30 days after the end of the interval. The parameters a and b are constants. The statistical significance of b indicates that the mean value of the average spread can predict a credit event. P takes on value 1 if a credit event occurs and 0 otherwise. In line with Finnerty et al. (2013) I expect the probability of a negative credit event to be higher than positive credit event after credit default swap spreads changes.

6 Results

6.1 One Sample T-test

6.1.1 Rating Changes

In order to investigate the first hypothesis, I conduct a one sample t-test on the cumulative abnormal returns within the constructed windows. In line with previous research, I expect there to be a significant positive abnormal returns in the case of downgrades and a significant negative abnormal returns in the case of upgrades. I do find evidence in favor of downgrades since the sign of the average cumulative abnormal returns is positive and the magnitude is significantly larger than 0 in all the windows, except for the month after the event. Specifically, I discover that the average cumulative abnormal return is larger than 0 before the event, reaching its peak in the [-60,-31] window at 4.277. Then it decreases before and on the event window, where it reaches a level of 2.775. The post-estimation window results show that the cumulative abnormal returns tend to decrease during the first months after the event and fall below 0 (however, the coefficient is not statistically significant in the [2,30] window) and then tend to reach the pre-event level. These results seem to show that downgrades have some informational content on the date of the announcement since I have positive cumulative abnormal return in the event window as well as afterwards. However, these overall results confirm the findings of previous studies that in the case of downgrades credit rating agencies tend to lag and not lead the credit default swaps market (Finnerty et al., 2013) (Norden & Weber, 2004) (Hull et al., 2004). In line with the majority of the previous literature, I find no significant evidence in favor of upgrades, although the sign of the cumulative abnormal return is in the expected direction in most windows .The only significant window is the [2;30] where the cumulative abnormal returns drop by -2.903 basis points. It seems like there is a delay in the market reaction, but then the average value of the CAR is very close to the event window CAR, even though there the values are not statistically significant. These results are presented in Table 4.

6.1.2 Reviews

The next test I perform is identical to the one above, except that it is applied to negative and positive reviews. Surprisingly, negative reviews seem to have a larger announcement effect than downgrades since the average cumulative abnormal return increases by 3.059 basis points. Since downgrades are often anticipated by reviews, they are not considered as surprising. However, since the difference of the abnormal returns between the [-30;-2] estimation window and the event window is negligible I am inclined to state that the credit default swaps market tends to lead the credit rating agencies since the abnormal returns before the market is significantly different from 0 and thus tends to be approximatively the same on the event date. On top of that, the cumulative abnormal return in the post-estimation window are not statistically significant, except in the second post-estimation window, where the average cumulative abnormal return results significantly different from 0, but lower than the event-window. These results are similar to Finnerty et al. (2013).

With regards to positive reviews, I find enough evidence to support the claim that credit rating agencies tend to lag the market as the average cumulative abnormal return is negative and statistically significant (-3.995) as of one month prior to the event. On the event date the average cumulative abnormal return decreases by 2.050 in the case of a positive review, which means that the market views positive reviews as a sign of relief. I also find some post-announcements effects whereby the average cumulative abnormal return is negative and significantly lower than 0, reaching its maximum after the first month from the credit rating announcement at -7.269. This may indicate a certain delay in the reaction of the credit default swaps market, which seems to fade away in the third month since the effect is smaller, similar to prior to the event, and statistically insignificant. These results are illustrated in Table 4.

Table 4: One sample T-tests of the cumulative abnormal returns in the event windows for all the rating events The null hypothesis is that the CAR is equal to 0.

	Event											
Window	**Downgrade**			**Upgrade**			**Negative Review**			**Positive Review**		
	CAR	**T-stat**	**N**	**CAR**	**T-stat**	**N**	**CAR**	**T-stat**	**N**	**CAR**	**T-stat**	**N**
[-90;-61]	1.550	2.011**	646	-1.700	-1.907*	473	1.346	1.402	402	-1.139	-0.756	142
[-60;-31]	4.277	3.933***	646	2.123	1.904*	473	2.534	2.428**	402	3.454	1.489	142
[-30;-2]	1.319	1.736*	646	-1.355	-1.591	473	3.331	3.407***	402	-3.995	-1.929*	142
[-1;1]	2.775	4.251***	646	-0.413	-0.988	473	3.059	3.642***	402	-2.050	-2.823***	142
[2;30]	-1.340	-1.336	646	-3.405	-2.903***	473	-1.082	-0.964	402	-7.269	-2.674***	142
[31;60]	1.891	2.619***	646	-0.528	-0.467	473	2.816	3.496***	402	-2.767	-1.14	142
[61;90]	2.895	3.644***	646	-0.782	-0.863	473	1.307	1.478	402	-1.265	-0.65	142

*** p<=0.01 ** p<=0.05 * p<=0.1

6.1.3 The effect of the crisis

In order to understand the effect of the crisis, I apply the test statistics described above to the three different periods. I find that downgrades have a larger effect during the crisis and that the credit default swaps market seems to be more attentive. The CAR in the event window is 4.822 basis points, whereas before the crisis is 3.192 basis points and after the crisis is 1.110 basis points. In the crisis, the average cumulative abnormal returns is statistically significant and larger than 0 for all the three windows prior to the event. The announcement has a lower effect since it was anticipated by the credit default swaps market. In particular, the anticipation seems to be greater two months before the event where the cumulative abnormal returns is 6.557 basis points higher on average. The tendency during the crisis seems to be slightly different in the period prior to the crisis since the credit default swaps market shows that there is a larger reaction during the announcement day rather than in the three months before. However, the announcement of a downgrade does not come as a complete surprise since the cumulative abnormal returns are different than 0 in the estimation windows prior to the event, although they are statistically significant two months before. On the contrary, in the pre-crisis period, I only find a significant pre-announcement effect in the [-60,-31] window, but I do not find any significant evidence of announcement-day effect. I find post-announcement day effect only two months after the event in the crisis period and in the second and third month in the post-crisis period. In this case, it could be interpreted again as a delayed reaction. With regards to upgrades, I find no statistically significant average cumulative abnormal returns on the event day with exception of the pre-crisis period where the mean is -2.173.

Other notable values are on the post-crisis period where there is a major drop in the month immediately after the event as the average CAR is -3.563 basis points. This means that the cumulative abnormal returns drop such an amount throughout the first month after the event on average. After this the CAR tends to rebound to the levels prior to the event, but these are not statistically significant and they have a positive sign. Finally, it can be seen that prior to the crisis there is a similar situation in the [31;60] window.

I also check whether the announcement day effect with regards to the reviews is amplified during the crisis. I do find evidence in the case of negative reviews where the average cumulative return in the event window is 5.142. This entails that on average the CAR increases by that amount in response to the announcement of a negative review. However, this value is lower than the previous month which indicates some anticipation effect. Finally, in the case of positive reviews I find evidence in favor of the information content hypothesis only in the post-crisis period where the cumulative abnormal return drops by -2.153 basis points on the [-1;1] window, which means that the credit default swaps market could not be expecting it to happen. These results are presented in Table 5.

Table 5: One sample T-tests specified across the three times period . Again, the null hypothesis is that CAR is 0.

		Period								
		Precrisis			**Crisis**			**Postcrisis**		
Event	**Window**	**CAR**	**T-stat**	**N**	**CAR**	**T-stat**	**N**	**CAR**	**T-stat**	**N**
Downgrade	[-90;-61]	0.779	0.481	112	3.101	2.433**	227	0.684	0.58	307
	[-60;-31]	2.957	2.406**	112	6.557	2.547**	227	3.072	2.592**	307
	[-30;-2]	1.144	0.914	112	4.439	2.913***	227	-0.925	-0.905	307
	[-1;1]	3.192	2.81***	112	4.822	3.079***	227	1.110	1.848	307
	[2;30]	-2.032	-1.934	112	0.570	0.318	227	-2.500	-1.567	307
	[31;60]	-1.348	-1.368	112	2.900	2.185**	227	2.327	2.117**	307
	[61;90]	-0.390	-0.468	112	0.479	0.687	227	5.880	3.806***	307
Upgrade	[-90;-61]	-1.599	-2.351**	108	-0.164	-0.091	94	-2.273	-1.623	271
	[-60;-31]	2.124	1.266	108	2.492	1.302	94	1.995	1.169	271
	[-30;-2]	-2.361	-1.524	108	-3.582	-1.42	94	-0.182	-0.177	271
	[-1;1]	-2.173	-2.619**	108	-0.428	-0.624	94	0.293	0.487	271
	[2;30]	-3.772	-1.645	108	-2.526	-0.936	94	-3.563	-2.256**	271
	[31;60]	-2.887	-2.043**	108	0.408	0.315	94	0.087	0.047	271
	[61;90]	-2.225	-1.741	108	-4.327	-2.271**	94	1.023	0.768	271
Negative Review	[-90;-61]	0.583	0.375	95	4.238	2.189**	141	-0.673	-0.492	166
	[-60;-31]	1.915	1.684	95	5.225	1.976	141	0.602	0.638	166
	[-30;-2]	3.961	3.334***	95	6.144	2.755***	141	0.580	0.476	166
	[-1;1]	2.416	1.838	95	5.142	2.627***	141	1.657	1.863	166
	[2;30]	-2.944	-1.23	95	0.147	0.077	141	-1.061	-0.625	166
	[31;60]	-0.691	-1.431	95	5.232	3.504***	141	2.771	1.929	166
	[61;90]	0.326	0.4	95	0.850	0.679	141	2.257	1.252	166
Positive Review	[-90;-61]	-2.079	-1.863	40	-4.106	-0.943	33	0.826	0.375	69
	[-60;-31]	3.189	1.052	40	6.466	1.696	33	2.168	0.533	69
	[-30;-2]	-3.764	-1.228	40	-5.929	-1.154	33	-3.204	-1.056	69
	[-1;1]	-2.201	-1.633	40	-1.651	-1.018	33	-2.153	-2.099**	69
	[2;30]	-9.930	-1.685	40	-1.676	-0.827	33	-8.402	-1.939	69
	[31;60]	-4.460	-1.326	40	1.740	0.377	33	-3.942	-0.974	69
	[61;90]	-1.591	-0.645	40	-10.243	-3.824***	33	3.217	0.942	69

*** p<=0.01 ** p<=0.05 * p<=0.1

6.2 Independent Sample T-test

Furthermore, I test whether there is an increased announcement effect for rising stars and fallen angels. Unfortunately, I do not find vast statistical evidence that can support the hypotheses, even though the direction and size of the cumulative abnormal returns are in the expected direction. These results are presented in Table 6. Only in the pre-crisis period the difference between rising stars and fallen angels is statistically significant. The average cumulative abnormal return for a company whose upgrade leads to an investment grade valuation is 6.001 basis points lower than for a fallen angel.

Table 6: Independent sample T-test of the cumulative abnormal returns in the case of rising stars or fallen angels. The Mean 1 refers to rising stars and Mean 0 refers to fallen angels.

RISING STAR-FALLEN ANGEL						
	Mean_1	N_1	Mean_0	N_0	Mean_Diff	T-test
Precrisis	-0.378	28	-6.379	93	-6.001	-3.172***
Crisis	-0.160	72	3.127	77	3.287	1.563
Postcrisis	-0.167	95	0.370	207	0.537	0.68

These results are further investigated by incorporating the size of the credit rating change. Unexpectedly and against prior evidence, I find that the difference in size of the rating does not seem to have a significant contribution in the case of downgrades. Only in the crisis period, the coefficient is positive and statistically significant, which means that a one unit rating change increases the average CAR by 7.878 basis points compared to an increase of more than one unit. In line with previous papers the coefficient does not have a significant effect in the case of upgrades. A similar explanation is provided by Steiner & Heinke (2001).

When testing the issuer nationality hypotheses, I find that there is significant evidence of a stronger market reaction for the US market due to lack of knowledge of the country specific credit regulations from the two agencies. Specifically, this is true solely for the post-crisis period and only for upgrades and downgrades, where the CAR on the announcement day increases by 1.919 and 2.148 basis points respectively. This is because the agencies are USA based and thus provide more revelatory ratings Steiner & Heinke (2001).

I then proceed to test the reliability hypothesis where I check whether there is a difference in returns according to the rating agency. In accordance to the previous literature, I do not find significant evidence except for negative reviews in the pre-crisis period whereby the difference in the average cumulative abnormal return is -4.573 basis points lower if the rating is given by S&P and for upgrades in the post-crisis period whereby the average cumulative abnormal return is 1.490 basis points higher if given by S&P. Finally, I broaden the analysis to a comparison between investment grade and speculative grade. I find that downgrades within the speculative grade class have a 7.833 basis points higher average cumulative return on the announcement day than downgrades within the investment grade class. This could be explained by the fact that while the investment grade obligations are still safe regardless of the rating, speculative grade obligations get closer to default every time there is a negative change in rating. I notice similar results for negative reviews whereby reviews that occur in the speculative grade realm are accompanied by an average CAR which is 3.394 basis points higher than the average CAR of a negative review in the investment grade. The difference CAR of the negative reviews is smaller than the difference CAR of the downgrades because reviews are warnings and not actual credit rating changes. Weirdly, positive reviews have a positive difference in the CAR as well when in the speculative grade. These results hold only for the pre-crisis period. All this is shown in Table 7.

Table 7: Independent sample T-test of the cumulative abnormal return in the event window in different samples defined by the dummy variables AGENCY, IGSG, USA and RSIZE. The null hypothesis is that the cumulative abnormal return is equal across every sample.

		Period																	
		Precrisis						**Crisis**						**Postcrisis**					
Variable	Event	Mean_1	N_1	Mean_0	N_2	Mean_Diff	T-Stat	Mean_1	N_1	Mean_0	N_2	Mean_Diff	T-Stat	Mean_1	N_1	Mean_0	N_2	Mean_Diff	T-Stat
AGENCY	Downgrade	-3.195	20	0.081	92	-3.277	-1.260	0.395	39	2.654	188	-2.259	-0.915	0.065	77	0.617	230	-0.552	-0.758
	Upgrade	-0.696	35	-0.511	73	-0.185	-0.251	-0.239	18	0.008	76	-0.246	-0.170	0.794	62	-0.696	209	1.490	1.835*
	Negative Review	-4.167	15	0.406	80	-4.573	-2.79***	0.139	28	2.774	113	-2.634	-0.946	0.317	61	1.696	105	-1.380	-1.631
	Positive Review	-1.836	15	0.606	25	-2.442	-1.684	-1.933	3	-0.932	30	-1.002	-0.444	-1.455	17	-0.970	52	-0.484	-0.438
IGSG	Downgrade	1.455	84	-6.379	28	7.833	3.572***	1.866	155	3.127	72	-1.260	-0.629	0.527	212	0.370	95	0.157	0.230
	Upgrade	-0.378	93	-1.767	15	1.389	1.406	-0.160	77	0.505	17	-0.665	-0.450	-0.167	207	-0.962	64	0.795	0.986
	Negative Review	0.227	82	-3.746	13	3.974	2.254**	2.523	124	0.262	17	2.261	0.661	1.078	144	1.918	22	-0.840	-0.694
	Positive Review	0.801	29	-3.238	11	4.038	2.706**	-1.721	21	0.199	12	-1.920	-1.468	-1.320	45	-0.658	24	-0.662	-0.664
USA	Downgrade	1.068	20	-0.845	92	1.914	0.732	1.216	38	2.477	189	-1.261	-0.504	1.892	105	-0.256	202	2.148	3.281***
	Upgrade	-0.618	28	-0.554	80	-0.064	-0.081	-0.249	33	0.074	61	-0.323	-0.271	1.161	57	-0.758	214	1.919	2.302**
	Negative Review	0.738	29	-0.779	66	1.517	1.131	-0.212	27	2.834	114	-3.046	-1.080	0.968	53	1.294	113	-0.326	-0.370
	Positive Review	-0.225	10	-0.338	30	0.114	0.068	-1.289	7	-0.951	26	-0.338	-0.212	-1.357	11	-1.039	58	-0.318	-0.244
RSIZE	Downgrade	-1.053	21	-0.377	91	-0.676	-0.263	8.687	42	0.808	185	7.878	3.358***	-0.088	53	0.597	254	-0.685	-0.820
	Upgrade	-0.764	11	-0.549	97	-0.215	-0.189	1.362	12	-0.245	82	1.607	0.947	-1.579	22	-0.247	249	-1.333	-1.063

*** p<=0.01 ** p<=0.05 * p<=0.1

t-statistics in parenthesis

6.3 Regression Results

In our cross sectional model, I regress the variables above on the cumulative abnormal returns on the day of the event itself. I find that the announcement of both upgrades and downgrades have a positive and statistically significant effect on the changes in credit default swaps. The magnitude of the coefficient is close to 1, which means that on average announcements of a downgrade lead to an increase of 1.278 basis points of the credit default swaps. This means that I am not induced to reject the information content hypothesis which says that the announcement of a credit rating change should be accompanied by changes in prices as they embody new information which would be not available to the public before. This is not surprising since the previous literature seem to agree that at least downgrades have a positive effect on price movements. However I do find evidence against the issuer nationality hypothesis since there is a lower price reaction for American issuers than for non-American issuers which could be due to different credit regulations abroad, even though the coefficient of $REVENT_i$ does not change drastically across the models. The addition of the country variable brings the average cumulative abnormal return close to 0 for U.S based issuers. The $RSIZE$ coefficient is not statistically significant in any of the regressions except for when the $IGSG$ variable is included. A rating change equal to one notch leads to a reduction of the CAR_reg1 by -1.964 basis points compared to a rating change larger than one notch. Besides, I do find evidence against the reliability hypothesis since I find that S&P rating changes are accompanied by a bigger market reaction than Moody'sAs shown, the CAR_reg1 increases by almost one basis point if the issuer is S&P. However, these results may be contaminated by the very large difference in observations between one agency and the other.The $IGSG$ variable is not statistically significant. Finally, $CRISIS$ variable is statistically significant. It results that on average during the crisis the cumulative abnormal return was 1.447 basis points higher than before and after the crisis. Overall adding new variables to our basic model does not have any major explanatory power as it can be noticed from the extremely small changes in the coefficients of our variables and in the adjusted R-squared of the model, which is extremely low. These results are presented in Table 8. When adding the interaction variables between the type of the event and the model I notice that there is no significant improvement in the model and thus it is not reported in the paper.

Table 8: Results of the regression analysis of upgrades and downgrades captured by the variable $REVENT_i$ on the cumulative abnormal returns on the day of the event. The table shows evidence in favor of the information content hypothesis as the coefficients of $REVENT_i$ are positive and statistically significant, although the model does not have increased explanatory power when adding control variables.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CAR_reg1	CAR_reg1	CAR_reg1	CAR_reg1	CAR_reg1
REVENT	1.278***	1.142***	1.106***	1.181***	0.965**
	(2.737)	(2.714)	(2.662)	(2.878)	(2.506)
RSIZE		-1.604	-1.691	-1.964*	-1.916
		(-1.324)	(-1.406)	(-1.647)	(-1.636)
USA			-1.147**	-1.027**	-1.079**
			(-2.545)	(-2.237)	(-2.370)
AGENCY			0.786*	0.964**	0.867*
			(1.788)	(2.046)	(1.901)
IGSG				-1.044	-1.020
				(-1.458)	(-1.435)
Crisis					1.447**
					(2.186)
Constant	-0.341	1.110	1.454	1.689	1.465
	(-1.428)	(0.994)	(1.375)	(1.623)	(1.458)
Observations	1,119	1,119	1,119	1,119	1,119
Adjusted R-squared	0.005	0.008	0.010	0.012	0.017

*** p<=0.01 ** p<=0.05 * p<=0.1

t-statistics in parenthesis

In the case of reviews, as shown in Table 9, I find that CAR_reg1 becomes 2.060 basis points larger in the case of negative reviews than positive reviews. USA does not have a statistically significant impact on the changes in credit spreads. Thus, I have to reject the issuer nationality hypothesis. However, $AGENCY$ has a statistically significant effect on CAR_reg1, which implies that S&P seems to be more reliable than Moody's and here I have to reject the reliability hypothesis. Finally whether the review for an upgrade or a downgrade entails a possible shift from the speculative grade to the investment grade does not seem to matter since the coefficient is statistically not significant. The coefficient of the crisis is not significant.

Table 9: Results of the regression analysis of positive and negative reviews captured by the variable $REVIEW_i$ on the cumulative abnormal returns on the day of the event. The table shows evidence in favor of the information content hypothesis as the coefficients of $REVIEW_i$ are positive and statistically significant.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CAR_reg1	CAR_reg1	CAR_reg1	CAR_reg1	CAR_reg1
REVIEW	2.060***	2.109***	2.127***	1.873***	1.760***
	(3.653)	(3.607)	(3.641)	(3.179)	(3.177)
USA		0.655	0.602	0.788	0.688
		(1.121)	(1.041)	(1.305)	(1.240)
AGENCY			1.847***	1.959***	1.835***
			(3.061)	(3.019)	(3.105)
IGSG				-1.338	-1.302
				(-1.487)	(-1.468)
Crisis					0.934
					(1.080)
Constant	-0.855**	-1.380**	-2.730***	-2.520***	-2.576***
	(-2.523)	(-2.523)	(-3.518)	(-3.495)	(-3.400)
Observations	544	544	544	544	544
Adjusted R-squared	0.011	0.010	0.018	0.020	0.021

*** p<=0.01 ** p<=0.05 * p<=0.1

t-statistics in parenthesis

6.4 Logistic Model Results

In this section, I present the results from four models, one for each type of rating event as shown in Table 10. I find that upgrades, downgrades, negative reviews can be forecast by looking at the changes in the movements in the credit default swap prices of the previous 30 days. I discover that changes in cds spreads are slightly better predictors of a negative review as the coefficient is 0.367. This means that a change in the movement of the credit default swaps by one basis point has a probability of 36.4% to be followed by a negative review. In the case of downgrades the probability of an event following one basis point increase in the movements of the credit default swaps spreads is 25.7%. On the contrary, an increase in the movements of credit default swaps spreads reduce the likelihood of an upgrade by 37.9%.

Table 10: Logistic results of the movements of the credit default swaps of the previous month and the probability of forecasting an event.

VARIABLES	(1) UPGRADE	(2) DOWNGRADE	(3) NEGATIVE REVIEW	(4) POSITIVE REVIEW
MEAN_CDS	-0.379**	0.257*	0.364**	-0.293
	(-2.404)	(1.909)	(2.147)	(-1.005)
Constant	-7.767***	-7.459***	-7.937***	-8.983***
	(-168.1)	(-188.4)	(-157.6)	(-106.0)
Observations	1,112,014	1,112,014	1,112,014	1,112,014
Pseudo R2	0.000690	0.000332	0.000634	0.000359

*** p<=0.01 ** p<=0.05 * p<=0.1

t-statistics in parenthesis

I enhance this analysis by incorporating the $CRISIS$ variable into the model. This allows to check whether the predictive power of the movements of the CDS spreads during the crisis is different than during the other period. The variable is positive and statistically significant in the negative events only. However its addition does not cause a major change in the main coefficient. These results are presented in Table 11.

Table 11: Results of the logistic model controlling for the crisis. The variable CRISIS takes on value 1 during the crisis and 0 otherwise.

VARIABLES	(1) UPGRADE	(2) DOWNGRADE	(3) NEGATIVE REVIEW	(4) POSITIVE REVIEW
MEAN_CDS	-0.379**	0.255*	0.362**	-0.293
	(-2.404)	(1.892)	(2.134)	(-1.007)
CRISIS	-0.0196	0.762***	0.755***	0.198
	(-0.170)	(9.219)	(7.200)	(0.995)
Constant	-7.763***	-7.666***	-8.142***	-9.026***
	(-150.5)	(-156.1)	(-130.7)	(-93.16)
Observations	1,112,014	1,112,014	1,112,014	1,112,014
Pseudo R2	0.000694	0.00745	0.00725	0.000701

*** p<=0.01 ** p<=0.05 * p<=0.1

t-statistics in parenthesis

7 Discussion and Conclusion

In this paper I investigate how the activities by credit rating agencies, specifically Moody's and S&P, changed throughout the crisis. I find that downgrades and negative reviews are perceived by the market more negatively than positive credit rating events as they are accompanied by greater negative abnormal returns. This effect is amplified throughout the crisis. Additionally, there is a tendency against the information content hypothesis as the market tends to anticipate credit rating events as there are significant abnormal returns in the windows. As a consequence, changes in credit default swap spreads prior to a credit rating event can be considered valid predictors of future credit events, especially in the case of negative reviews. This is something that was never discovered before.

Furthermore, this study is innovative as it integrates the methodology of two different studies. Applying the methodology of Steiner & Heinke (2001) to Hull et al. (2004) I come up with five different hypothesis. I find mixed evidence in favor of the information content hypothesis as with downgrades, negative reviews and positive reviews there is some anticipation from the market starting at least one month before the event. I do not find evidence in favor of the issuer nationality hypothesis which could be attributed to difference in regulations. I find evidence against the reliability hypothesis whereby the cumulative abnormal returns are higher if the announcement is given by S&P. I find evidence against the price pressure hypothesis as the coefficient of the IGSG is negative, but not statistically significant. I find that when incorporating the effect of the crisis into the model the cumulative abnormal returns increase by 1.45 basis points compared to the precrisis and the postcrisis in the case of downgrades and upgrades.

The tendency of rating agencies to lag the market helps to think that movements of credit default swaps spreads are good predictors of future events. I do find evidence in favor for all the events except for positive reviews, which is something that previous papers did not find.

7.1 Limitations & Future Research

This paper, however, is not without limitations. In particular, the data collecting process is troublesome as there is a very uneven amount of observations across rating agencies, thus it would be recommended to use data coming from the agencies themselves. Moreover, using an Index to retrieve company data may not be optimal, thus future research could use different sources of data. Using alternative data could be useful as the companies in the index are the biggest companies in the world and this does not allow to control for their size, which could serve as an additional control variable that could increase the validity of the model. Other suggestions would be to control for company specific characteristics that the agencies use to determine the credit rating, such the debt ratio. The analysis could further be expanded by incorporating industry effects so that it would be possible to check whether companies belonging to some industries are more sensitive than others. Finally, one could think of conducting a break point analysis in order to narrow down the current event study to specific days of the investigated period.

All in all, this study brings new insights saying that credit ratings may not be as powerful informational tools, but are good forecasting tools from an asset pricing perspective, however it could be expanded by incorporating more corporate finance notions as well as company specific characteristics.

8 Appendix

Table A1: The values reported under skewness and kurtosis are the probabilities that the distribution of the dependent variable follows a normal distribution,which is characterized by a skewness coefficient equal to 0 and a kurtosis coefficient equal to 3.

Jacques-Bera Test for Normal Data			
Variable	Obs	Skewness	Kurtosis
$(CAR_{i[t_1;t_2]})$	768	0.000	0.000

Table A2: This test checks whether the variances of the samples constructed through the dummies are equal by relaxing the normality assumption

Levene's test for homogeneity of variances		
Variable	F-statistics	p-value
USA	1.646	0.200
RSIZE	0.031	0.860
AGENCY	2.372	0.125
IGSG	23.150	0.000

Table A3: The value reported under W is the Shapiro–Wilk statistic and the value V is a parameter that indicates the departure from normality.

Shapiro-Wilk Test for normal data					
Variable	Obs	W	V	z	Prob>z
e	544	0.434	205.487	12.850	0.000

Table A4: The VIF (variance inflation factor) is the ratio of the variance of the model with all the variables by the ratio of the variance of the model with only the main independent variable. As a rule of thumb if the VIF index is smaller than 10, there is no evidence of multicollinearity.

Multicollinearity-VIF		
Variable	VIF	1/VIF
IGSG	1.1	0.913
USA	1.04	0.934
CRISIS	1.04	0.963
REVIEW	1.07	0.958
AGENCY	1.04	0.974
Mean Vif	1.05	

Table A5: The null hypothesis is that the variance of the error term is equal across observations. Since the p-value is smaller than 0.05, I have to reject the null hypothesis and find evidence in favour of heteroskedasticity.

Breush-Pagan test for Heteroskedasticity	
H_0: Homoskedasticity	
H_a: Heteroskedasticity	
χ^2	4.63
Prob> χ^2	0.031

Table A6: Results of the White's test for homoskedasticity. This test relaxes the normality assumption. As the p-value is larger than 0.05, I cannot reject the null hypothesis that there is homoskedasticity.

White's test	
H_0: Homoskedasticity	
H_a: Heteroskedasticity	
χ^2	13.65
Prob>	0.552

Table A7: Results of the Wooldrige's test for autocorrelation. As the p-value is smaller than 0.05, I have to reject the null hypothesis that there is no autocorrelation.

Wooldridge's test	
H_0: No Autocorrelation	
H_a: Autocorreation	
$F(1, 344)$	28.596
Prob>	0.000

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